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China's Transport Land: Spatiotemporal Expansion Characteristics and Driving Mechanism

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Abstract: The literature about changes in land use includes many studies of global sustainable development goals, while studies of transport land expansion have been relatively scarce. In this paper, we present an analysis of the spatiotemporal characteristics of transport land expansion in China's 31 provinces from 2009 to 2017, applying the spatial Dubin model to identify the factors that influenced changes in per capita transport land area (*PCTLA*). The eastern and western regions have continued to lead the nation in terms of the total area dedicated to transport land. The expansion speed of transport land in the central and western regions, however, has been faster than in the eastern and northeast regions. As for *PCTLA*, the western region had the greatest amount and the central region the least. Further, *PCTLA* showed significant spatial autocorrelation. Economic development, government regulations, industrial structure, and the extent of opening up and urbanization had significant positive impacts on *PCTLA*, while the development of railway freight had a negative impact. This paper concludes with some policy suggestions for optimizing transport investment, accelerating the adjustment of industrial structure and transport structure, and implementing high-quality urbanization. The results should be of interest to those involved in the sustainable development of transport systems.

Keywords: transport land; spatiotemporal characteristics; spatial Durbin model

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1. Introduction

Since the 1990s, global-resource and environmental problems have progressively worsened. At present, land use change is a matter of concern to researchers [1,2] who have studied it from the perspectives of spatiotemporal patterns [3–8], driving factors [3,7,9–11], and specific land types, including urban [12–16], industrial [17–19], agricultural [20–23], ecological [24–26], and transport land [27]. Overall, scholars have tended to focus on analyzing the expansion of urban and industrial land or changes in agricultural and ecological land while paying relatively little attention to the expansion of transport land.

The Chinese transport industry has been experiencing rapid growth since the implementation of the reform and opening-up policy [28]. However, it has been facing problems associated with the limited availability of land. From 2009 to 2017, the total area of transport land in China increased by 35.8%, from 28,232 to 38,335 km^2 [29], a higher rate of growth than those for other construction lands, such as residential, independent industrial, mining, forest, and garden land [29]. With the steady progress in the urbanization process, the tension between the needs for transport land and for agricultural lands, in particular, cultivated and forest land, is expected to intensify over the foreseeable future. Accordingly, scientific and rational analyses of the spatiotemporal characteristics of transport land in China and the driving mechanisms behind them are of considerable practical significance for efforts to maximize the utilization of land resources.

For this study, we quantitatively analyzed transport land expansion in China's 31 provinces from 2009 to 2017. This paper helps to fill several gaps in the literature on transport land. In the first place, few studies have been conducted on transport land in China, and none have yet to comprehensively discuss the mechanisms driving its expansion. The present study addresses the spatiotemporal characteristics of transport land in China by presenting a comparative examination of the influences of multiple factors on changes in it. Second, currently, many studies have focused on the driving factors behind changes in land use based on quantitative analysis methods [11]. For example, Liu et al. [3] analyzed the driving forces of land use change in northeastern China during 1990–2000 by canonical correlation analysis. On the basis of establishing the principal component analysis, Li et al. [9] studied the driving forces of land use change in the Longitudinal Range-Gorge in China. Jiang et al. [10] analyzed the driving force of land use/land cover change in the Xishuangbanna region from 1986–2008 by using gray incidence analysis as the analytical method. Applying the analytical tool of Geodetector, Liu et al. [11] studied the driving factors of land use change in the Henan province from 1995 to 2015. Overall, many studies have neglected the spatial effect [3,9,10], and only few studies have considered the spatial effect [11]. According to the Tobler's law, geographical distance has a direct effect on the correlation of things; in other words, the closer the distance, the stronger the correlation [30]. To the best of our knowledge, this study is the first to make use of the spatial Durbin model (SDM) to empirically analyze the factors that influence changes in transport land use in China. This model accounts for the spatial interactions among the explanatory and explained variables [31,32]. The third contribution of this paper is to propose a series of development policies for improving the intensive use of transport land that can inform national and local policies regarding transport land.

In what follows, Section 2 describes the sources of the data and selection of the indicator. Section 3 presents the methodology, and Section 4 presents the empirical analysis. In Section 5, we summarize our conclusions and discuss the policy implications of our work. Figure 1 shows the organization of the paper schematically.

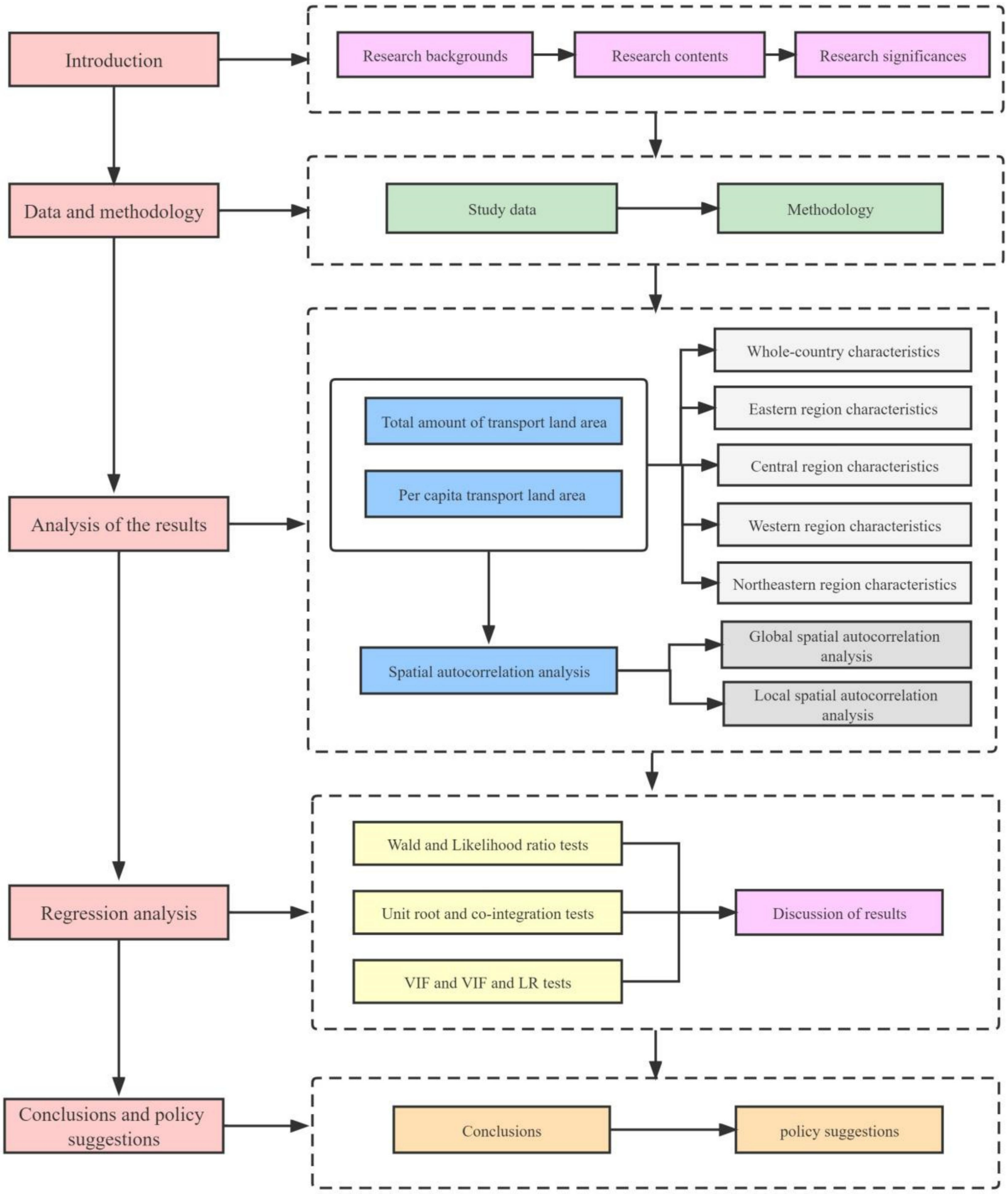

Figure 1. Flowchart of the present study.

2. Data and Methodology

2.1. Data

For this study, we conducted an empirical analysis of the factors driving the expansion of transport land in the 31 Chinese provinces from 2009 to 2017. Compared with changes in the total volume of transport, per capita transport land area (*PCTLA*) provides a more accurate picture of the extent of transport land expansion. Therefore, we selected this measure as the dependent variable in the regression model, defining it as the ratio of the total amount of transport land to the permanent resident population. For convenience in discussing the overall trends, we assigned the 31 provinces based on their locations to one of four regions, either eastern, central, western, or northeast China (Figure 2). Following previous studies, we selected economic development level (DEL), government regulations (GR), industrial structure (IS), transport structure (TS), opening up level (OUL), and urbanization level (UL) as the driving factors for the regression analysis. These data were obtained from the China Statistical Yearbook (2010–2018) [33], China Land and

Resources Statistical Yearbook (2015–2017) [29], and the Statistical Bureau of China (NBSC) (2022) [34].

Figure 2. Diagram of China's four regional economic zones. Data source: NBSC (2022) [34].

Economic development has both positive and negative effects on the expansion of transport land. On the one hand, it brings the application of advanced production technologies and management methods, leading to more intensive or sparing land use. Conversely, the development of the social economy correlates with the demand for transport [28], thus leading to the expansion of transport land. For these reasons, the impact of economic development on *PCTLA* is a matter of considerable interest in urban planning.

Local governments in China have always played an essential role in economic life, in particular, by determining the initial distribution of resources [35]. Governments finance the construction, transformation, and expansion of transport infrastructure, which promotes the expansion of transport land. Therefore, government expenditures can serve to represent the impact of government behavior on this form of expansion.

Generally, the demand for freight in secondary industries is greater than that in tertiary industries. Thus, the development of secondary industries promotes the expansion of transport land. In other words, the industrial structure in an area impacts the expansion of transport land therein. Accordingly, we measured industrial structure for this study as the proportion of GDP attributable to the secondary industry.

Railways, compared with roadways, offer greater loading capacity and speed and therefore play a larger role in government behavior and land conservation. The transport structure then impacts the expansion of transport land. We measured transport structure for this study as the proportion of the railway freight volume to total freight volume.

Opening up to the outside world has been beneficial to China in terms of acquiring and implementing advanced technologies that originated in other economies, thus giving better play to the comparative advantages through trade [36,37]. These steps are conducive to the optimal allocation of various resources, including to transport land and the conservation of land. An effective transport system is a prerequisite for such opening up, and establishing one naturally means increasing the use of land for the transport of goods and people. Therefore, we used the extent of opening up to the outside world as a dependent variable affecting the amount of *PCTLA*.

Urbanization likewise increases the demand for transport land, especially when it is rapid [28,38–40]; thus, we selected the extent of urbanization as a control variable (Table 1).

Table 1. Influencing factors.

Explanatory Variable	Definition and of the Variables	Pre-Judgment
Economic development level (EDL)	GDP per capita (10^4 RMB)	Unknown
Government regulation (IS)	Proportion of financial expenditures to GDP (%)	Positive
Industrial structure (IS)	Proportion of the added value of tertiary industry to GDP (%)	Positive
Transport structure (TS)	Proportion of railway freight volume to total freight volume (%)	Negative
Opening up level (OUL)	Proportion of foreign trade to GDP (%)	Unknown
Urbanization level (UL)	Proportion of the urban resident population to the total population (%)	Positive

Data source: China Statistical Yearbook (2010–2018) [33], China Land and Resources Statistical Yearbook (2015–2017) [29], and NBSC (2022) [34].

2.2. Methodology

2.2.1. Spatial Autocorrelation Analysis

Before the regression analysis, a spatial autocorrelation analysis of *PCTLA* was conducted. Significant positive spatial autocorrelation in *PCTLA* would mean that the spatial regression models outperformed the general regression models [40–42]. We used the *Global Moran's I* Index to test the spatial dependence of regional *PCTLA*, expressing the formula as:

$$Global\ Moran'I = \frac{\sum_{i=1}^{N}\sum_{j=1}^{N} Wi,j\left(PCTLAi,t - \overline{PCTLAt}\right)\left(EEPCTLAj,t - \overline{PCTLAt}\right)}{\left[\frac{1}{N}\sum_{i=1}^{N}\left(PCTLAi,t - \overline{PCTLAt}\right)^2\right]\sum_{i=1}^{N}\sum_{j=1}^{N} Wi,j} \tag{1}$$

$PCTLA_i$ and $PCTLA_j$: the *PCTLA* of provinces *i* and *j*;
n: the number of provinces;
W_{ij}: the spatial weight matrix such that if province *i* is adjacent to province *j*, W_{ij} = 1; otherwise, W_{ij} = 0. Further,
$\overline{PCTLA}$: average value of the *PCTLA*.

The *Global Moran's I* values range from −1 to 1 and, when greater than 0, indicate positive spatial dependence of *PCTLA*. When the *Global Moran's I* value is less than 0, the spatial distribution of *PCTLA* shows a negative spatial autocorrelation. When the value is 0, there is no spatial dependence, and *PCTLA* exhibits a random spatial distribution.

The *Global Moran's I* Index then reveals the overall spatial agglomeration characteristics but not the local agglomeration characteristics [43]. The *Local Moran's I* Index reflects the degree of spatial correlation between a given province and surrounding provinces [44] and is calculated as:

$$Local\ Moran'I = \frac{N\left(PCTLAi,t - \overline{PCTLAt}\right)\sum_{j=1}^{N} Wi,j\left(EEPCTLAj,t - \overline{PCTLAt}\right)}{\sum_{i=1}^{N}\left(PCTLAi,t - \overline{PCTLAt}\right)^2} \tag{2}$$

When the value of the *Local Moran's I* Index in province *i* is greater than 0, the *PCTLA* there is similar to that in the surrounding provinces; otherwise, the *PCTLA* is dissimilar. A Moran scatter plot (MSP) and local indicators of spatial association (LISA) maps usually serve to measure the local spatial autocorrelation index. There are four quadrants in the scatterplot map. The dots in the first quadrant, in which high *PCTLAs* are surrounded by other high *PCTLAs* to form high–high (HH) agglomeration areas, and the third quadrant, in which low *PTCLAs* are surrounded by other low *PCTLAs* to form low–low (LL) agglomeration areas, represent positive spatial correlations above or below the average value, respectively. The dots in the second quadrant, in which high *PCTLAs* are surrounded by low *PCTLAs* to form high–low (HL) agglomeration areas, and the fourth quadrant, in which low *PCTLAs* are surrounded by high *PCTLAs* to form low–high (LH) agglomeration areas, represent negative spatial correlations.

2.2.2. Spatial Durbin Model (SDM)

The spatial econometric model has proved effective in accounting for the spatial dependence and correlation among the variables being investigated [45,46]. For the needs of the research, the SDM was applied to analyze the factors driving changes in *PCTLA* in China. Elhorst [47] distinguished three types of spatial econometric models, including and in addition to the SDM, spatial lag models (SLMs) and spatial error models (SEMs). An SLM—also referred to as a spatial autoregressive model (SAR)—includes the endogenous interaction effects among the dependent variables [48,49] and can be expressed as:

$$Y = \rho WY + \beta X + \varepsilon \tag{3}$$

where Y stands for the explained variable, X indicates the independent variable, ρ indicates the spatial autoregression coefficient, β denotes the regression coefficient of the independent variable, W denotes the spatial weight matrix, and ε is a random error term. The main use of SLMs was to determine whether the independent variables in a given region were affected by the independent variables in neighboring regions [50].

An SEM can be expressed as:

$$\begin{cases} Y = \beta X + \varepsilon \\ \varepsilon = \lambda W\varepsilon + \mu \end{cases} \tag{4}$$

where λ denotes the spatial error coefficient of the explained variable vector, μ stands for a disturbance term [46], and all of the other variables have the same connotations that they have in Equation (6). An SEM is especially suitable for situations in which the omitted variables cause regional interaction effects in both local and adjacent areas [48].

An SDM accounts for the spatial interaction effect between the explained variable and all of the explanatory variables [47] and can be expressed as:

$$Y = \rho WY + \beta X + \theta WX + \varepsilon \tag{5}$$

where θ represents the spatial lag coefficient of the independent variable to be estimated, and all of the other variables have the same connotations that they have in Equations (3) and (4). SDMs can be effective in realizing the complementary advantages of SLMs and SEMs [51].

3. Analysis of the Results

3.1. Total Amount of Transport Land Area

3.1.1. Whole-Country Characteristics

During the research period from 2009 to 2017, the total scale of transport land in China increased rapidly across all four regions, although in distinct ways. On a national level, transport land area reached what was then a record 38,335 km^2 in 2017 from 28,232 km^2 in 2009, for an average annual growth rate of 3.9%. As can be seen in Figures 3 and 4, the western region has the largest transport land area, followed by the eastern, central, and northeastern regions. The average annual growth rate in transport land area in these regions was 3.35%, 4.29%, 2.26%, and 4.77%, respectively, over the research period.

Figure 3. Transport land area in the 31 Chinese provinces in 2017. Data source: China Land and Resources Statistical Yearbook (2015–2017) [29].

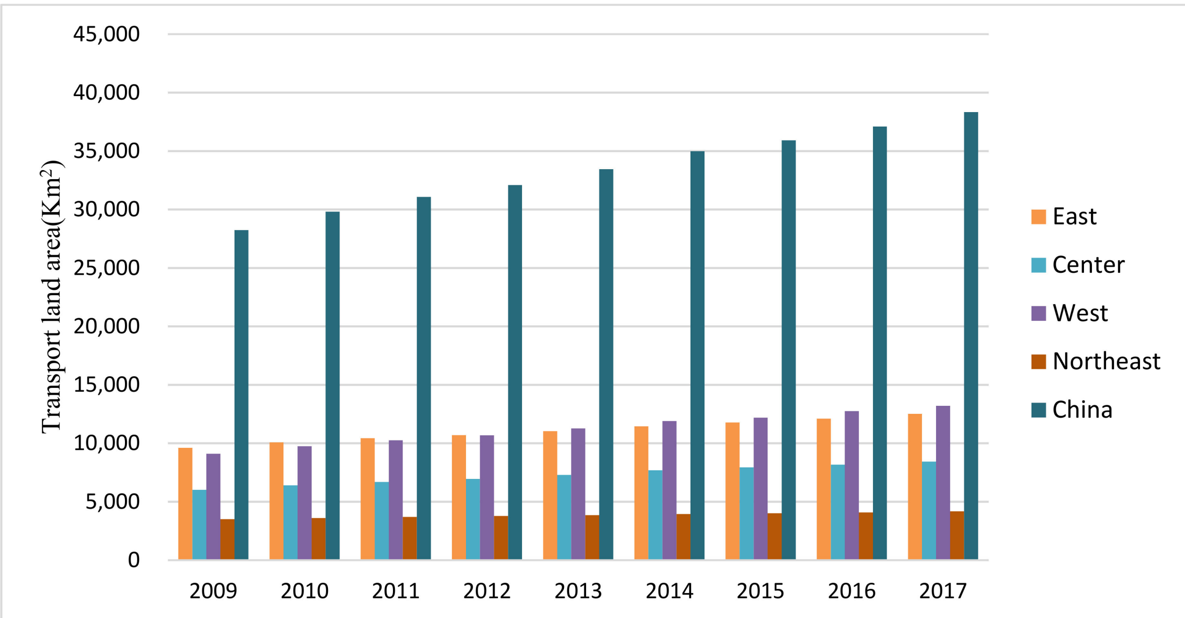

Figure 4. Evolutionary trend in transport land in the four Chinese regions from 2009 to 2017. Data source: China Land and Resources Statistical Yearbook (2015–2017) [29] and NBSC (2022) [34].

3.1.2. Eastern Region Characteristics

The area of transport land in the eastern region increased from 9612 km^2 in 2009 to 12,514 km^2 in 2017, or 30.2%. This region is the country's most developed economically, with the most concentrated population and highest level of social development [52,53]. It is now experiencing steady acceleration of its industrialization and urbanization. The resulting explosive growth in the demand for transport has led to the expansion of transport land. However, many parts of the eastern region are zoned functionally as priority development areas, a designation that requires particularly strict control of the supply of construction land. Thus, the expansion of transport land in the region has been below the national average, accounting for 34.0% of total Chinese transport land in 2009 but only 32.6% in 2017. Among the areas showing notably rapid expansion in transport land have been Jiangsu, Shandong, Fujian, and Hainan.

3.1.3. Central Region Characteristics

The central region is important as the center of commodity grain production in China. The government's policies for protecting cultivated land are sufficiently stringent in affecting the expansion of transport land here to some extent. However, with the implementation of the "Strategies for the Middle Rises", China has increased investment in transport infrastructure in the region, thereby promoting the expansion of transport land. From 2009 to 2017, the total area of transport land in the region increased by 8429 km^2 to 6021 km^2, or 40%, which is greater than the national average. In addition, over this period, the transport land area in Henan was the largest in the region and that in Shanxi was the smallest. Jiangxi had the fastest growth rate, and Hunan had the slowest.

3.1.4. Western Region Characteristics

The western region has been the least economically developed in the country, although it possesses vast land resources. In the late 1990s, the government implemented its Western Development Strategy, increasing investment in the region and, in turn, the demand for passengers and goods and expansion of the transport land area. Thus, from 2009 to 2017, the transport land area in the western region increased from 9099.25 km^2 to 13,207.93 km^2, or 45.2%, far exceeding the national average. Inner Mongolia had the largest transport land area in the region, while Tibet, Qinghai, and Ningxia had the smallest areas. The growth rate of the transport land in Guizhou, Gansu, Qinghai, and Xinjiang over the research period was especially rapid at more than 50%, far greater than the national average.

3.1.5. Northeastern Region Characteristics

The northeastern region is China's traditional industrial base but has experienced a deep recession and has been slowly losing population. Accordingly, from 2009 to 2017, the transport land area in the region increased from 3499.58 to 4183.87 km^2, or 19.55%, the smallest increase among the four regions. In 2017, the transport land areas of Liaoning, Jilin, and Heilongjiang were 1636, 965.67, and 1582 km^2, having increased by 23.43%, 21.58%, and 14.66%, respectively, over the period of the study, in each case less than the national average.

3.2. Per Capita Transport Land Area (PCTLA)

3.2.1. The Whole Country Characteristics

China's *PCTLA* overall showed an upward trend, increasing from 21.2 km^2/person in 2009 to 27.4 km^2/person in 2017, or 29.2% (Table 2). The standard deviation of the *PCTLA*s across all 31 provinces also showed an increasing trend, increasing from 20.7 in 2009 to 25.3 in 2017. These results indicate that the variation in the *PCTLA* from province to province likewise increased.

Table 2. The values of *PCTLA* for 31 provinces in China from 2009 to 2017 (m^2).

Regions	Provinces	2009	2010	2011	2012	2013	2014	2015	2016	2017	Mean
East	Beijing	15.7	15.4	15.0	15.1	14.9	14.9	14.8	15.0	15.1	15.1
	Tianjin	17.9	18.3	18.6	18.3	18.6	18.7	19.1	19.2	19.5	18.7
	Hebei	21.9	22.5	22.8	23.2	23.7	24.7	25.3	25.7	25.9	24.0
	Shanghai	11.3	11.2	11.5	11.5	12.2	12.2	12.4	12.5	12.7	12.0
	Jiangsu	23.6	24.5	25.0	25.5	26.1	26.9	27.5	28.1	29.0	26.2
	Zhejiang	22.2	22.6	23.4	23.9	24.6	25.4	25.9	26.5	26.8	24.6
	Fujian	22.7	24.8	26.3	27.3	28.4	29.9	31.2	32.2	33.5	28.5
	Shandong	19.8	20.1	20.4	20.7	20.9	21.3	21.5	21.7	22.4	21.0
	Guangdong	13.9	14.2	14.8	15.0	15.5	16.2	16.5	17.0	17.5	15.6
	Hainan	20.9	22.3	23.1	23.8	24.8	26.0	27.2	27.8	29.8	25.1
	Mean	19.0	19.6	20.1	20.4	21.0	21.6	22.1	22.6	23.2	21.1
Central	Shanxi	22.6	22.8	23.3	24.7	26.5	27.9	28.3	28.8	29.2	26.0
	Anhui	17.3	18.7	19.6	20.5	21.0	22.0	22.4	23.2	23.9	21.0
	Jiangxi	17.0	18.6	19.9	20.5	21.2	22.6	23.9	24.5	25.0	21.5
	Henan	15.1	15.9	16.7	17.1	18.0	18.8	19.1	19.0	19.8	17.7
	Hubei	15.6	16.5	16.8	17.6	18.8	20.1	20.7	21.7	22.3	18.9
	Hunan	17.2	18.2	19.0	19.2	19.7	20.3	20.7	21.2	21.6	19.7
	Mean	17.5	18.5	19.2	19.9	20.9	21.9	22.5	23.1	23.7	20.8
West	Inner Mongolia	69.9	73.1	74.4	75.7	79.9	83.0	85.0	90.7	92.5	80.5
	Guangxi	22.0	24.2	25.5	26.8	27.1	27.8	28.0	28.5	29.2	26.6
	Chongqing	15.4	16.6	17.4	18.2	19.1	19.8	20.3	20.8	21.3	18.8
	Sichuan	13.3	15.2	15.9	16.3	16.9	17.7	18.0	18.4	18.9	16.7
	Guizhou	15.9	18.0	20.2	21.6	23.4	26.3	26.9	28.4	29.9	23.4
	Yunnan	19.7	20.1	21.1	21.4	21.9	23.1	23.6	24.2	25.1	22.2
	Tibet	112.7	112.1	114.6	113.2	113.9	115.3	115.8	124.5	125.1	116.3
	Shaanxi	22.0	23.0	23.5	24.6	25.5	26.8	27.4	28.0	28.5	25.5
	Gansu	22.9	24.2	26.1	27.3	29.1	30.8	31.4	32.8	33.8	28.7
	Qinghai	59.3	63.8	67.0	68.3	77.4	83.4	83.6	88.1	89.2	75.6
	Ningxia	44.9	46.8	47.8	49.5	51.8	54.0	55.4	57.6	59.6	51.9
	Xinjiang	44.9	50.3	53.0	56.0	60.2	62.0	61.9	63.4	65.4	57.5
	Mean	38.6	40.6	42.2	43.2	45.5	47.5	48.1	50.4	51.5	45.3
Northeast	Liaoning	30.5	31.1	31.9	33.0	33.6	34.3	35.2	35.8	37.4	33.7
	Jilin	29.0	29.3	30.4	30.8	31.8	33.1	33.5	34.6	35.5	32.0
	Heilongjiang	36.1	37.3	38.2	38.8	39.2	39.8	40.7	41.4	41.8	39.2
	Mean	31.9	32.6	33.5	34.2	34.9	35.7	36.5	37.3	38.2	35.0
China		21.2	22.2	23.0	23.6	24.5	25.4	26.0	26.6	27.4	24.4

Data source: China Land and Resources Statistical Yearbook (2015–2017) [29] and NBSC (2022) [34].

3.2.2. Eastern Region Characteristics

The annual average *PCTLA* of the provinces in the eastern region during the research period ranged from 15.1 to 28.5 km^2/person. In this region, Beijing and Shanghai have relatively low *PCTLAs* while Jiangsu, Zhejiang, and Fujian have relatively high *PCTLA*s. Notably, the *PCTLA* in Beijing showed an initial downward trend followed by an upward trend over the research period. The *PCTLA*s in other eastern provinces showed an upward trend. As the nation's capital, Beijing has maintained tight control over the supply of various types of construction land, including transport land. However, in recent years, the implementation of policies targeting "noncapital" functions and a strict household register system have limited the growth of the resident population—which even decreased in 2017—while, to some extent, promoting growth in *PCTLA* in the period after 2011.

3.2.3. Central Region Characteristics

The central region had the smallest *PCTLA* in China. In 2017, the average *PCTLA* across the central provinces was only 23.7 km^2/person, ranging from 19.8 km^2/person in Henan to 29.2 km^2/person in Shanxi (Figure 5). Conversely, Shanxi had the smallest total area of transport land in the region, 1081.87 km^2, and Henan had the greatest at 1894.87 km^2. The large population of Henan (in 2017, the province's permanent resident population reached 95.59 million, third only to Shandong and Guangdong in the Eastern region) was using a relatively small *PCTLA*.

Figure 5. Average *PCTLA* values in 31 Chinese provinces in km^2/person (2009–2017). Data source: China Land and Resources Statistical Yearbook (2015–2017) [29] and NBSC (2022) [34].

3.2.4. Western Region Characteristics

The *PCTLA* of the western region was the largest in China, averaging 51.5 km^2/person, far above the national average. As noted, the country's western development strategy has resulted in a rapid increase in the total scale of transport land in the region. The population of the western region, however, is smaller than that of the eastern and central regions; thus, the *PCTLA* of the western region has been growing rapidly. Of the western provinces, Inner Mongolia, Tibet, Qinghai, and Xinjiang—China's four largest provinces, all with low population densities—had the highest *PCTLA*s. Conversely, Sichuan and the municipality of Chongqing had the largest permanent populations among the western provinces and, accordingly, relatively low *PCTLA*s.

3.2.5. Northeastern Region Characteristics

The average *PCTLA* of the provinces in northeastern China was greater than the national average. In 2017, the *PCTLA*s for Liaoning, Heilongjiang and Jilin were 35.77, 34.59, and 41.43 km^2/person, respectively. The region is known as China's "eldest son". Since 2000, the northeast region has lacked economic vitality however and has experienced significant population loss or limited growth. In particular, decreases in the resident populations of Liaoning and Heilongjiang since 2015 and 2014, respectively, have contributed to the increases in the *PCTLA* of the region.

3.3. Spatial Autocorrelation Analysis

3.3.1. Global Spatial Autocorrelation Analysis

We calculated the *Global Moran's I* Index for the overall *PCTLA* based on Equation (1), as shown in Table 3. Over the period of the study, the overall index of the *PCTLA* was positive at a significance level of 1%, meaning that the overall *PCTLA* for China's 31 provinces showed significant positive spatial autocorrelation from 2009 to 2017, and the spatial distribution pattern showed a strong spatial agglomeration mode. More specifically, the *Global Moran's I* Index of China's *PCTLA* showed an upward trend from 2009 to 2014, increasing from 0.271 to 0.352, indicating that the provinces with similar *PCTLA*s became more clustered geographically. However, the index of China's *PCTLA* then decreased to 0.338 in 2017, indicating a weakened spatial autocorrelation.

Table 3. Value of the *Global Moran's I* of provincial *PCTLA* in China (2009–2017).

Year	*Moran's I*	Z-Score	*p*-Value
2009	0.271 ***	3.058	0.002
2010	0.296 ***	3.209	0.001
2011	0.307 ***	3.303	0.001
2012	0.322 ***	3.392	0.001
2013	0.346 ***	3.528	0.001
2014	0.352 ***	3.549	0.000
2015	0.346 ***	3.489	0.000
2016	0.334 ***	3.405	0.001
2017	0.338 ***	3.422	0.001

Note: *** stands for significance at the 1% level.

3.3.2. Local Spatial Autocorrelation Analysis

We further used the Moran scatterplot and the local indicators of spatial association (LISA) to test for local spatial agglomeration. Figures 6–8 present the Moran scatterplot of the *PCTLA* in China for 2009, 2013, and 2017, respectively. As these figures show, in 2009, there were eight provinces (Inner Mongolia, Liaoning, Jilin, Heilongjiang, Tibet, Qinghai, Ningxia, and Xinjiang) in the first quadrant and four (Shanxi, Sichuan, Yunnan, and Gansu) in the second, with the remaining 19 provinces falling in the third quadrant. Thus, the provinces located in the first and third quadrants made up approximately 25.8% and 61.3% of the total sample provinces, respectively. In 2013, Jilin shifted from the first quadrant to the second and Shanxi from the third quadrant to the second; the other provinces remained in the same quadrants. In 2016, no province shifted. Overall, most of the provinces were in the first and third quadrants over the research period, indicating that the spatial homogeneity was more significant than the spatial heterogeneity for the *PCTLA*.

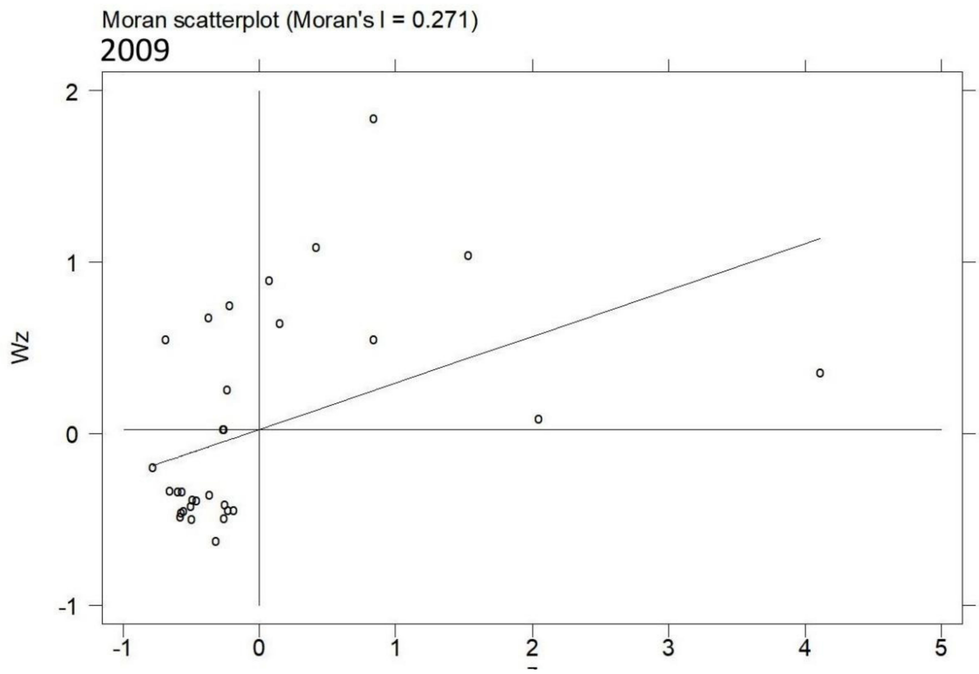

Figure 6. Moran scatterplot of the *PCTLA*s in the 31 Chinese provinces in 2009.

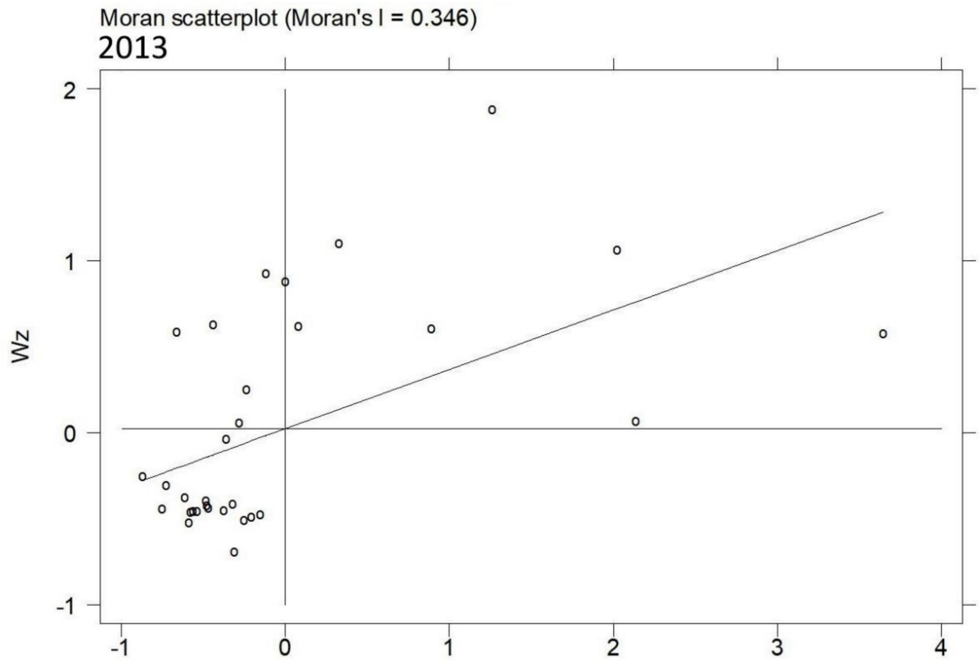

Figure 7. Moran scatterplot of the *PCTLA*s in the 31 Chinese provinces in 2013.

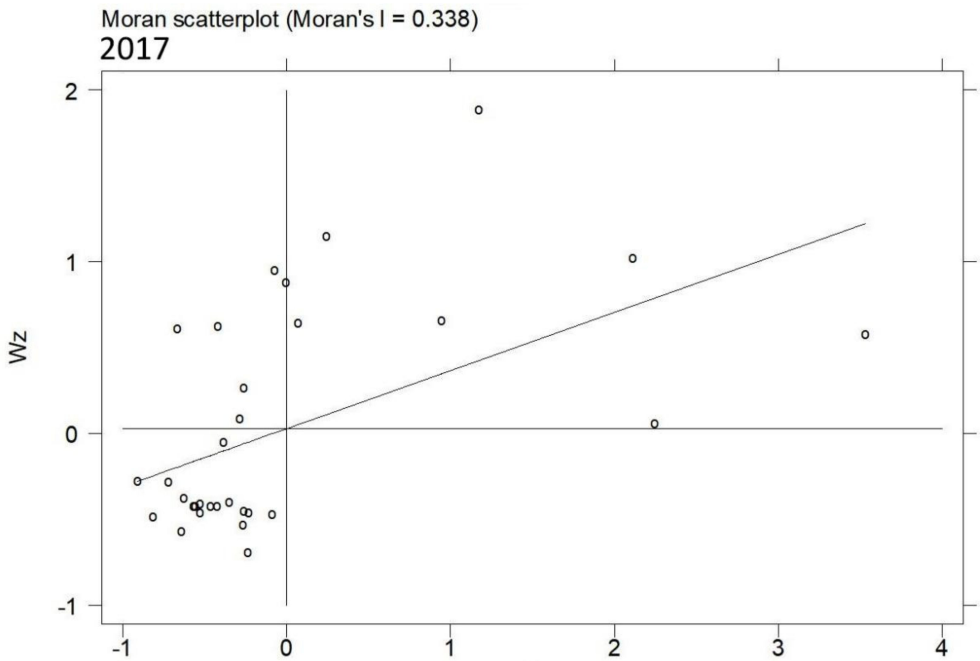

Figure 8. Moran scatterplot of the *PCTLA*s in the 31 Chinese provinces in 2017.

4. Regression Analysis

4.1. Wald and Likelihood Ratio Tests

The above analysis characterized the *PCTLA* in China based on significant spatial correlation and dependence. Thus, there was the possibility of parameter estimation errors when applying ordinary regression models, and thus, the spatial econometric model was applied to determine the factors driving *PCTLA* empirically. First, we employed the Wald and likelihood ratio (LR) tests to determine whether the SDM could degenerate into the SLM or SEM. As Table 4 shows, the test statistics of Wald–lag, LR–lag, Wald–error, and LR–error were at the 1% level of significance, meaning that the SDM was the appropriate spatial econometric model, rather than the SLM or SEM. Next, it was essential to apply the

Hausman test to determine whether the SDM should use the random effects or the fixed effects. The Hausman test value of 64.69 (p = 0.000) indicated that the fixed effects should be used.

Table 4. The regression results of the likelihood ratio test and Wald test.

	Fixed Effects	Random Effects
Wald test spatial lag	70.96 ***	58.97 ***
LR test spatial lag	62.93 ***	53.24 ***
Wald test spatial error	64.25 ***	58.35 ***
LR test spatial error	62.06 ***	63.52 ***

Note: *** stands for significance at the 1% level.

4.2. Unit Root and Co-Integration Tests

Before performing the SDM regression analysis, we first examined the stationarity of all of the variables using the LLC, IPS, Fisher–ADF, and PP–ADF methods, our aim here being to prevent spurious regression [54]. Table 5 shows the results of the panel unit root testing, which indicated that all of the variables were second-order stable and that we could proceed with the co-integration test. A Kao co-integration then served to check for a long-run equilibrium relationship among any of the variables. The results showed that there was a co-integration relationship, with a possibility of being rejected at the 5% significance level (t statistic = −2.743 **). Thus, a co-integration relationship existed between the *PCTLA* and its driving factors during the research period.

Table 5. The results of the unit root test.

	LLC	IPS	Fisher-ADF	PP-ADF
PCTLA	−6.60768 ***	1.83930	64.6650	124.415 ***
DEL	7.04412	10.9454	35.6990	75.7464
GR	−4.12454 ***	0.64406	64.2165	75.4905
IS	0.33945	4.68552	23.7020	18.0197
OUL	−3.38313 ***	−0.00699	63.9570	55.9228
UL	0.43679	3.09024	60.6950	128.335 ***
TS	−10.8097 ***	−2.46638 ***	96.8195 ***	124.508 ***
△*PCTLA*	−18.6607 ***	−7.64791 ***	183.482 ***	207.988 ***
△DEL	−1.67760 **	−1.20650	109.696 ***	138.485 ***
△GR	−11.2683 ***	−4.49974 ***	132.641 ***	179.111 ***
△IS	−8.07446 ***	−2.37604 *	95.5379 **	163.830 ***
△OUL	−13.5558 ***	−6.10816 ***	160.520 ***	202.712 ***
△UL	−43.1966 ***	−15.2702 ***	231.852 ***	264.114 ***
△TS	−12.3195 ***	−3.62334 ***	121.600 ***	157.152 ***
△△*PCTLA*	−19.1019 ***	−7.11403 ***	178.995 ***	258.801 ***
△△DEL	−20.3399 ***	−7.36711 ***	175.295 ***	215.905 ***
△△GR	−20.3610 ***	−7.47487 ***	190.048 ***	300.100 ***
△△IS	−22.9412 ***	−5.83187 ***	146.495 ***	159.424 ***
△△OUL	−11.1121 ***	−3.23622 ***	111.226 ***	149.422 ***
△△UL	−41.3933 ***	−14.0336 ***	251.204 ***	300.619 ***
△△TS	−18.7076 ***	−7.19147 ***	181.980 ***	269.499 ***

Note: ***, **, * represent variables significantly at 1%, 5%, and 10%, respectively.

4.3. VIF and LR Tests

In order to check for the possibility of multicollinearity among the variables, we conducted variance inflation factor (VIF) tests. As Table 6 shows, all of the VIF values for the independent variable were less than 9, indicating that there was not multicollinearity among the variables. Next, we conducted the SDM regression analysis using STATA 13.0. Following Equation (5), the explicit regression equation for the SDM with fixed effects is:

$$PCTLA_{i,t} = \rho \times WPCTLA_{i,t} + \beta_1 \times DEL_{i,t} + \beta_2 \times GR_{i,t} + \beta_3 \times IS_{i,t} + \beta_4 \times OUL_{i,t} + \beta_5 \times UL_{i,t} + \beta_6 \times TS_{i,t} + \theta_1 \times WDEL_{i,t} + \theta_2 \times WGR_{i,t} + \theta_3 \times WIS_{i,t} + \theta_4 \times WOUL_{i,t} + \theta_5 \times WUL_{i,t} + \theta_6 \times WTS_{i,t} + \varepsilon_{i,t}$$
$$\varepsilon_{i,t} \sim N(0,\sigma^2{}_{i,t}\,In), \quad (6)$$

where DEL, GR, IS, OUL, UL, and TS refer to economic development, government regulation, industrial structure, opening up level, urbanization, and transport structure, respectively, and ε is the stochastic disturbance item.

Table 6. The VIF test.

	DEL	GR	IS	OUL	UL	TS	Mean VIF
VIF	5.91	1.95	1.49	3.13	8.45	1.49	3.74
1/VIF	0.169	0.514	0.669	0.319	0.118	0.669	

Table 7 displays the estimation results of spatial fixed effects, time fixed effects, and spatial and time fixed effects. The LR test results of spatial fixed effects (chi2 (14) = 24.28, p = 0.042) and time fixed effects (chi2 (14) = 975.17, p = 0.000) imply that the SDM with the spatial and time fixed effects have a higher accuracy of parametric estimation. Additionally, the Log-likelihood values shown in Table 7 indicate that the spatial and time fixed effects demonstrated better fit than the other two effects. Therefore, the best procedure was to employ the SDM with spatial and time fixed effects for the empirical analysis.

Table 7. The regression results of SDM.

	Spatial Fixed Effects	Time Fixed Effects	Spatial and Time Fixed Effects
DEL	6.162 ***	2.579 ***	2.563 ***
GR	96.775 ***	12.651 **	17.451 ***
IS	79.956 ***	10.895 **	9.853 **
OUL	−18.485 ***	8.675 ***	7.993 ***
UL	−0.296	36.232 ***	40.009 ***
TS	32.632 ***	−44.135 ***	−46.854 ***
W*DEL	−12.447 ***	−4.058 ***	−4.041 ***
W*GR	25.776 *	46.310 ***	63.479 ***
W*IS	67.294 ***	−18.218 ***	−18.856 *
W*OUL	37.527 ***	−11.969 ***	−13.642
W*UL	97.730 ***	7.953	14.247 ***
W*TS	21.284	29.439 ***	17.175
Spatial rho	0.169 **	0.327 ***	0.207 **
Variance sigma2_e	88.135 ***	2.861 ***	2.665 ***
R-squared	0.199 ***	0.731	0.729
Log-likelihood	−1021.641 ***	−546.195	−534.057

Note: ***, **, * represent variables significantly at 1%, 5%, and 10%, respectively.

4.4. Discussion of Results

The economic development level correlated positively with the *PCTLA*, reaching a significant level ($p < 0.01$). The economic growth increased government revenue as well as the demand for effective infrastructure, which, in turn, stimulated investment in transport infrastructure [55,56] and the dedication of more land to transport. China's rapid economic development since the implementation of reform and opening-up policies in the previous century has resulted in strong financial support for the construction of transport infrastructure.

Government intervention was significant at the 1% level, with a regression coefficient of 17.45. The intervention of national fiscal policy has caused the transport infrastructure network in China to become increasingly integrated [57] but also to occupy considerable land resources. It is, therefore, necessary to further the transformation of the expansion of transport land from extensive to intensive.

The industrial structure correlated positively with the *PCTLA* at a statistically significant level ($p < 0.05$). China has created the world's largest manufacturing economy and, as a result, an enormous logistical demand on secondary industry. As the economy and the process of urbanization in China continue to expand, so will logistical demands and, in turn, the need to increase the supply of transport land.

The estimated coefficient of the transport structure was significantly negative at the 1% level. In China, road freight is the most important component of transport freightage, at 39.57 billion tons, while railway freight in the volume is not dominant, at only 4.03 billion tons (7.8% of the total). In order to support intensive land use and conserve transport land, railway freight must become a priority.

Opening up correlated positively with the *PCTLA*, being significant at the 1% level. In order to develop an export-oriented economy, China has built a great deal of transport infrastructure, including roads, railways, and ports, and this effort has led to the rapid expansion of transport land. Further, the regression coefficient of the urbanization level was significantly positive as a result of China's rapid economic growth. At the same time, the amount of transport land has continued to increase rapidly in recent years. It was necessary for the government to promote the intensive use of transport land to ensure high-quality urbanization.

5. Conclusions and Policy Suggestions

The rapid recent increase in transport infrastructure construction in China has not only promoted economic growth, reduced transportation costs, and enhanced regional economic ties [57], it has also created many problems, including a rapid increase in transport land. In this paper, the spatial expansion characteristics of transport land and the factors driving *PCTLA* were analyzed.

The results of the research showed, to begin with, that the overall growth in the amount of transport land in China has been rapid, exceeding that of industrial and residential land. There are clear regional variations in this trend however: the total amount of transport land in the eastern and western regions was large, while the increase in transport land in the central and western regions was faster than that in the eastern and northeast regions. Second, regarding *PCTLA*, the western region had a relatively high level and the central region had a relatively low level. The global spatial autocorrelation test showed that the *PCTLA* had significant spatial agglomeration characteristics, with adjacent provinces tending to have similar *PCTLA*s. The local spatial autocorrelation test located most Chinese provinces in the first and third quadrants during the study period, indicating that the spatial homogeneity was more significant than the spatial heterogeneity in relation to *PCTLA*. Third, the SDM regression results showed that economic development, government regulations, industrial structure, opening up, and urbanization had significantly positive impacts on the amount of *PCTLA*, while the railway freight mode had a negative impact.

We offer the following policy suggestions based on the findings presented in this paper; first, the relevant government departments can improve the situation by insisting on strict administrative oversight and approval of transport construction projects in order to protect farmland, make the most of spending on transportation, and increase investment in railways, waterways, and other transport modes that minimize the demand for transport land; second, industrial structure adjustments and the vigorous development of high-tech industries can enhance the value of industrial products; third, in terms of transport structure, promoting a shift in the preferred long-distance freight mode from roadways to railways or waterways and vigorously developing multi-modal transport can increase the efficiency with which transport land is used; fourth, furthering the process of opening up, importing advanced transport engineering technology and management technology from other countries, and rational planning of special transport routes and ports for foreign trade can facilitate the effort to preserve land resources; fifth, a new path to urbanization that involves greater attention to conserving transport land and promoting intensive utilization rather than haphazardly expanding transport infrastructure. Therefore, the construction of transportation infrastructure needs to be carried out more intelligently, and urban as well as rural roads should be built reasonably.

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